

Advanced Methods for Passive Acoustic Detection, Classification, and Localization of Marine Mammals

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LONG-TERM GOALS

For effective long-term passive acoustic monitoring of today's large data sets, automated algorithms must provide the ability to detect and classify marine mammal vocalizations and ultimately, in some cases, provide data for estimating the population density of the species present. In recent years, researchers have developed a number of algorithms for detecting calls and classifying them to species or species group (such as beaked whales). Algorithms must be robust in real ocean environments where non-Gaussian and non-stationary noise sources, especially vocalizations from similar species, pose significant challenges. In this project, we are developing improved methods for detection, classification, and localization of many types of marine mammal sounds.

OBJECTIVES

We are developing advanced real-time passive acoustic marine mammal detection, classification, and localization methods using a two-pronged approach: developing improved DCL algorithms, and developing standardized interfaces and software.

First, we are developing, testing, and characterizing advanced DCL algorithms:

1. Echolocation click classification. Algorithms are being developed and tested for several species of beaked whales and small odontocetes.
2. Tonal signal detection and classification. Algorithms are being tested for several species of mysticetes and for small odontocetes.
3. Multi-sensor localization. Algorithms will be developed and tested on datasets containing sounds of both odontocetes and mysticetes.

Second, improved DCL software will be developed and both existing and new methods will be made available to users. The key contribution will be the development of four well-specified interfaces, for detection, feature extraction, classification, and localization.

APPROACH

Odontocete click detection and classification. A multi-class support vector machine (SVM) classifier was previously developed (Jarvis et al. 2008). This classifier both detects and classifies echolocation clicks from five species of odontocetes, including Blainville's and Cuvier's beaked whales, Risso's dolphins, short-finned pilot whales, and sperm whales. Here Moretti's group, particularly S. Jarvis, is improving the SVM classifier by resolving confusion between species whose clicks overlap in frequency.

The current real-time system of Roch et al. for odontocete click classification is based on Gaussian mixture models (GMMs) using cepstral feature vectors. Cepstral feature vectors provide a compact representation of the spectrum (Rabiner and Juang 1993) that let the system represent echolocation spectra using a reduced number of coefficients, providing a lower-dimensional feature space than using a standard representation of the spectrum. This system will be extended to cover more species and more recording/noise environments. In a separate project, Roch is working with personnel at Univ. Calif. San Diego on developing new features based on subspace models and improved noise compensation. The subspace models use hierarchical principal components analysis and random-

projection trees (Freund et al. 2007) to learn new feature sets that will be used in place of cepstral feature vectors. The noise modeling will examine how to more effectively estimate background noise and compensate for it, taking into account interactions between noise and source (Ross 1976).

Tonal signal detection and classification. “Tonal signal” is a generic term for frequency-modulated calls such as mysticete moans or odontocete whistles. Methods for detecting and classifying such sounds are being developed and applied to both odontocete whistles and baleen whale vocalizations, including minke (*Balaenoptera acutorostrata*), blue (*B. musculus*), and humpback (*Megaptera novaeangliae*) whales.

Odontocete click removal. The methods being developed here classify (to the species level) the odontocete whistles that are extracted automatically via the *Silbido* tonal contour following system (Roch et al. 2010). Research led by Roch focuses on the areas of signal processing and *Silbido*’s search algorithm to further refine this algorithm. Echolocation clicks result in broad-band energy producing interfering peaks in the time-frequency domain. These are being mitigated by locating echolocation clicks through an existing detection algorithm (Soldevilla et al. 2008, Roch et al. 2011) based on Teager energy (Kaiser 1990, Kandia and Stylianou 2006), and then removing it by interpolation.

In observing expert analysts classify whistles to species, we have noted that experts tend to comment on the general shape of a whistle. Extracted contours will be classified to species using hidden Markov models (HMMs) which are capable of modeling temporal transitions, thus exploiting the shape. HMMs have been used previously to classify signature whistles to groups, but a general approach requires more general models that can capture inter-specific variation. We propose segmenting whistles into components based upon easily identifiable landmarks (e.g. inflection points), and creating multiple models for components based upon cluster analysis.

Baleen whale vocalizations. Methods developed here for baleen whale detection and classification are based on automated detection and classification of minke whale ‘boing’ vocalizations using tonal signal methods which have been previously applied to US Navy hydrophone data at PMRF (Mellinger et al. 2011; Martin et al. 2013). The dominant spectral component (DSC, described in Martin et al. 2013) is used for detection of the call, as this component is typically the last component detected at long ranges (> 30 km). Minke boing call detection is used here has a first-stage detection step similar to the tonal detection processing described by Mellinger et al. (2011). A second stage is also used which processes a frequency band from 1320 to 1450 Hz to detect the onset frequency-modulation (FM) upsweep component of the call to obtain a more accurate estimate of the start time of the call for later localization processing. Then a third stage calculates the frequency with high spectral resolution (0.72 Hz per bin) of the DSC for each detected boing to help associate calls from individuals and in some cases to help track individuals over multiple hours.

Advanced localization algorithms. The first requirement for passive acoustic localization of marine mammals is the need to associate the detection of an individual signal as it is received across the array of widely spaced hydrophones. Moretti is leading the effort to develop a nearest-neighbor approach to detection association. This approach still uses TDOA/hyperbolic methods, but will not discard TDOA from pairs of detections when the normally requisite 3 detections are not achieved. Rather, detections from a given hydrophone will be associated with detections from all of its nearest neighbors and pairwise TDOAs will be calculated.

Software and interfaces. An Application Programming Interface (API) is a specification of a set of procedure calls (for objects, methods), data types (scalars, structures, classes, etc.), and protocols for use of the procedures and data types, making it relatively simple for a developer to add new algorithms to an existing system. Ishmael's (Mellinger 2001) interfaces for detection and localization comprise a relatively complex set of object class methods (procedure calls) and data types; although it is standardized, it is hardly straightforward or well-documented. The M3R system (Morrissey et al. 2006) has a format for standardized data serving and detection message passing. We are developing and testing APIs for these systems.

WORK COMPLETED

Meetings, data sharing site, and funding:

- (1) We have had teleconference meetings approximately monthly to discuss both technical details and project logistics, with a face-to-face meeting on 3-Nov-2013 at the ASA meeting.
- (2) We established a private Internet-accessible site for sharing data sets, meeting minutes, and code. The site is private since some of the data, while not classified, is considered sensitive.
- (3) Funding for the first three years of the project reached all project members. Year-4 funding is working its way through financial systems to reach project members OSU and SDSU.

RESULTS

Detection/classification algorithms: tonal sounds. Advanced automated detection/classification methods have been developed and applied to fin, sei, Bryde's, minke, and humpback whales (Fig. 1). The minke algorithm includes detection of minke boing calls, while the other detections are more generic: for humpback song units between 200 Hz and 1200 Hz, and for fin, sei, and Bryde's whale calls between approximately 15 Hz and 50 Hz. Humpback whale song unit processing is also done using the Generalized Power Law (GPL) detector (Helble 2012). Improvements include a common parallel-processing front end.

Another approach to whistle classification has concentrated on increasing the purity of the automatically generated whistle clusters prior to training hidden Markov models. We also completed work on exploiting ridge information in spectrograms to help identify delphinid whistles (Kershenbaum and Roch, 2013). By looking at a spectrogram as a topological map, it is possible to examine the direction in gradient vectors and look for coherent regions where the signs of the gradient vectors swap. This algorithm has been incorporated into our whistle extraction algorithm *Silbido* (Roch et al., 2011a). Work on unsupervised clustering of whistles was also refined. The techniques have been evaluated on spinner (*Stenella longirostris*), common (*Delphinus spp.*), and bottlenose dolphins (*Tursiops truncatus*); all show potential for stable unsupervised whistle component clustering (Fig. 2).

Detection/classification algorithms: odontocete clicks. An iterative normalized least mean squares (NLMS) method and a subspace-based method – to separate a raw audio stream into ‘noise’ and ‘signal’ components – were developed for noise reduction in ocean recordings. Although the methods are not capable of completely separating clicks from noise, they do improve the signal-to-noise ratio of the clicks and help improve detection performance. A new detector was developed using NLMS and the noise-subspace method combined with the existing energy ratio mapping algorithm (ERMA)

detector (Klinck and Mellinger 2011). This combination improved overall performance at detecting clicks of Blainville's beaked whales in noise. A paper on this was written (Lu et al. in prep.).

Blainville's beaked whales generate homing pulses, termed buzzes, prior to prey capture attempts. Buzz clicks not only are produced at a significantly faster inter-click interval ($ICI_{buzz} \ll ICI_{forage}$), but the structure of the click is also different (Jarvis et al. 2008). A class-specific support vector machine (CS-SVM) classifier (Jarvis 2012) was developed specifically for *Md* buzz clicks. However, since buzzes have a much lower source level than foraging clicks, the detection threshold of the buzz classifier must be set correspondingly lower. Running the buzz class, with its very low threshold, continuously can cause an unacceptably high number of false alarms. To avoid this problem, the buzz classifier is launched only after a *Md* foraging click-train has been detected (i.e., 80% of all the clicks detected in the past 20 s have been classified as *Md* foraging clicks). Then the buzz classifier runs for only 30 minutes, the average vocal period of an *Md* dive. See Figs. 3-5.

Localization and tracking. Humpback song unit automated localizations are being investigated via cross correlation of GPL outputs, rather than spectrograms or raw time series, and are showing promise. GPL processing appears to work in the presence of Navy MFAS activity.

Two model-based localization methods have been developed for baleen whale localization. One uses detection start times and associations to determine time difference of arrivals, while the second uses cross-correlation of call *sequences* between hydrophone pairs. The Matlab implementation of the first method was initially pursued on this effort with new capabilities (e.g., depth estimation) and refinements being done in collaboration with an LMR project (see Related Projects, below). By automatically associating sequential localizations to individual whales, additional information on the species is available such as acoustic ecology (e.g. call rates) and kinematic behavior (e.g. speed, depth, heading rates). This may be termed 'tracking' of individuals and serves to automate what humans do visually when presented time sequences (time) of whale localizations presented on nautical charts (space).

For minke, fin, sei, Bryde's, and humpback whales, rudimentary kinematic tracking of individual whales enabled automatic call interval analysis. Call intervals automatically obtained not only helped confirm the species, but also added information on the species' call rates and behavior.

Last year a number of advances were made on localization of beaked whales using time differences of arrival (TDOAs) gained from widely spaced sensors (Baggenstoss in press). A difficulty that occurs in localization is the large number of ambiguous solutions (Fig. 6), arising from false time-delay measurements arise when the TDOA is measured between clicks or click-trains from different sources, different propagation paths, or different periods of a given click train. The method developed here is an efficient algorithm that can efficiently track multiple whales in real time. Our approach uses a multi-hypothesis tracker (MHT) with pruning to maintain a large number (thousands) of candidate tracks. With each new update, each track is updated as a Kalman filter using several potential associations, then candidate tracks are pruned. Examples are shown in Figs. 7-8. The track position of a DTAGged whale obtained from the MHT algorithm compared favorably to the ground truth position data from the tag (Figs. 9-10).

Software: The architecture for writing detection, classification, and localization modules has been completed and communication between Ishmael and PAMGUARD and a test module has been established. The architecture provides a translation library for each DCL platform supported that

marshals data into a format that can be shared with other processes. Modules run as separate programs that share a limited region of memory with the DCL platform. This allows modules written on platforms that require separate processes (e.g. Matlab, R) to be gracefully handled. Users designing classification modules will configure the DCL platform to send data to their module and make calls to a standard interface library. Results are sent back to the DCL platform in a similar manner. The plug-in architecture has been demonstrated with pass through (identity function) modules in Java and C. Ongoing work is developing interfaces to handle event processing such as passing detections or localizations to PAMGUARD/Ishmael for further processing.

IMPACT/APPLICATIONS

For the Navy, passive acoustic monitoring (PAM) provides a means of long-term monitoring of many cetacean populations, especially over areas of high interest. Such areas are repeatedly subjected to Navy exercises involving intense sounds, especially multi-ship mid-frequency active (MFA) sonar. Currently, required environmental monitoring is dependent primarily on visual line transect surveys that are costly and, in the case of aerial surveys, significantly dangerous. In both the areas critical to the Navy and in other areas critical to marine mammals, PAM is dependent on automated DCL methods. The advanced DCL algorithms being developed here will make PAM more effective and efficient; the algorithm implementations across standardized interfaces that handle both real-time and pre-recorded data streams from diverse platforms will make them available to Navy fleet operators as well as the wider marine mammal research community.

TRANSITIONS

Both model-based localization algorithms have been transitioned to an Operations and Maintenance Navy (OMN)-funded effort monitoring for marine mammals in the Hawaii Range Complex (see Related Projects).

The automated methods for detecting and localizing baleen whales in this effort have transitioned to funded efforts monitoring for marine mammals during U.S. Navy training activity at the Pacific Missile Range Facility in the Hawaii Range Complex. (Martin et al. 2014 in prep).

RELATED PROJECTS

“Passive Autonomous Acoustic Monitoring of Marine Mammals with Seagliders” (N00014-10-1-0387) award to Mellinger (and Klinck). The methods developed here are likely to be implemented in the Seaglider acoustic system for real-time detection and classification of marine mammal sounds.

“Acoustic Metadata Management and Transparent Access to Networked Oceanographic Data Sets” (NOPP N00014-11-1-0697) award to PI Marie Roch, Co-PI Simone Baumann-Pickering, John A. Hildebrand, et al. A metadata management system is being developed, which allows access to locally stored acoustic detections and metadata and links in a standardized way to external sources, such as oceanographic or ephemeris data. We will design our DCL plugins to provide outputs that can easily be stored in the acoustic metadata database.

“PMRF acoustic data collection and analysis” (N000701WR4C673) OMN funded effort supporting COMPACFLT’s Hawaii Range Complex monitoring of marine mammals during training activities.

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- Jarvis, S.M., Morrissey, R.P., Moretti, D.J. 2014. Marine Mammal Monitoring on Navy Ranges (M3R): A toolset for automated detection, localization, and monitoring of marine mammals in open ocean environments. Marine Technology Society Journal, Volume 48, Number 1, January/February 2014, pp. 5-20(16).
- Lu, Y., Klinck, H., and Mellinger, D.K. In prep. Noise reduction for better detection of beaked whale clicks. Submitted to J. Acoust. Soc. Am.
- Martin, S.W., T.A. Marques, L. Thomas, R.P. Morrissey, S. Jarvis, N. DiMarzio, D. Moretti, and D.K. Mellinger. 2012. Estimating minke whale (*Balaenoptera acutorostrata*) boing sound density using passive acoustic sensors. Marine Mamm. Sci. doi:10.1111/j.1748-7692.2011.00561.x, online first 23-Apr-2012.
- Matsumoto, H., C. Jones, H. Klinck, D.K. Mellinger, and R.P. Dziak. 2013. Tracking beaked whales with a passive acoustic profiler float. J. Acoust. Soc. Am. 133(2):731-740.
- Mellinger, D.K., M.A. Roch, E.-M. Nosal, and H. Klinck. In prep. Signal processing. Chapter for *Listening in the Ocean*, M. Lammers and W. Au, eds. Submitted to editors.

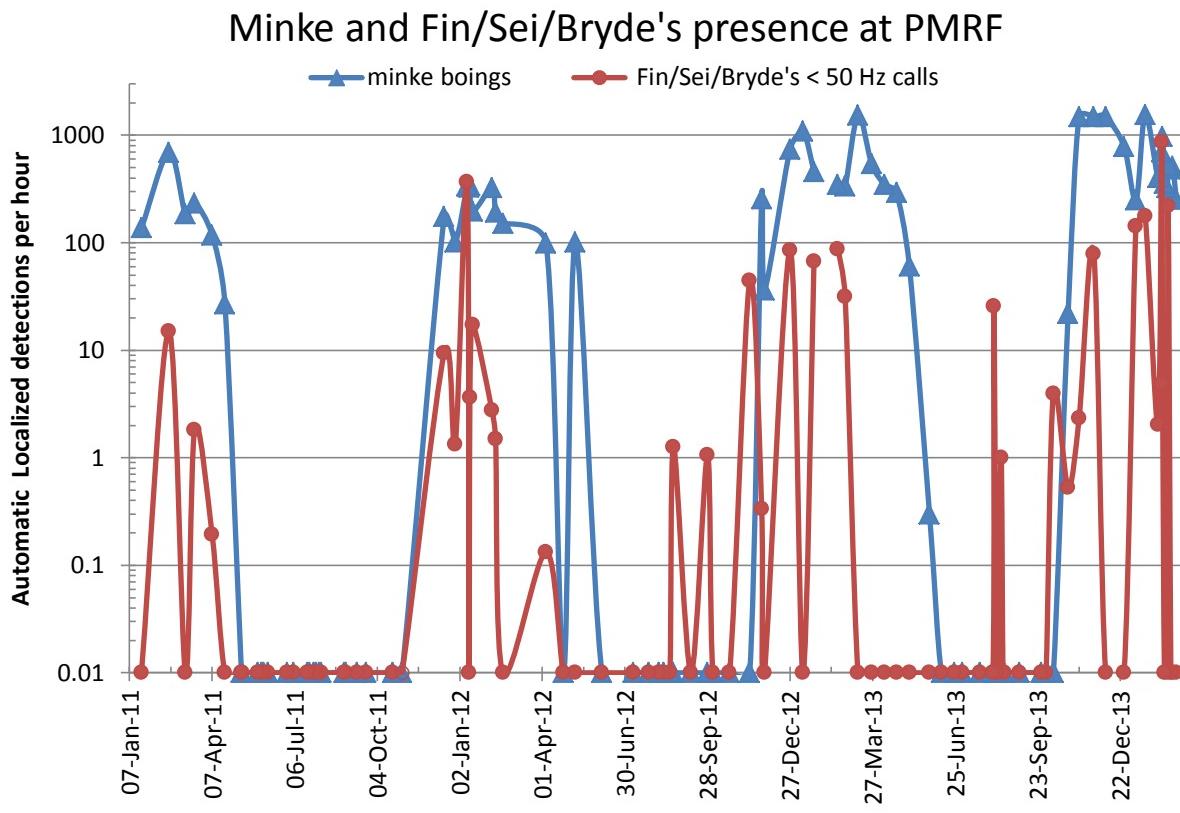


Figure 1. Minke, fin, sei, and Bryde's whales automatically localized detections per hour for 3366 h of data from Jan 2011 to Feb 2014. Strong seasonal presence for the majority of the data with suggestions that minke are more abundant due to the higher counts. Data for Aug 6, 2013 has been confirmed to be similar calls to those reported for Bryde's. Zero calls shown as 0.01 per h for the semi-log scale plot.

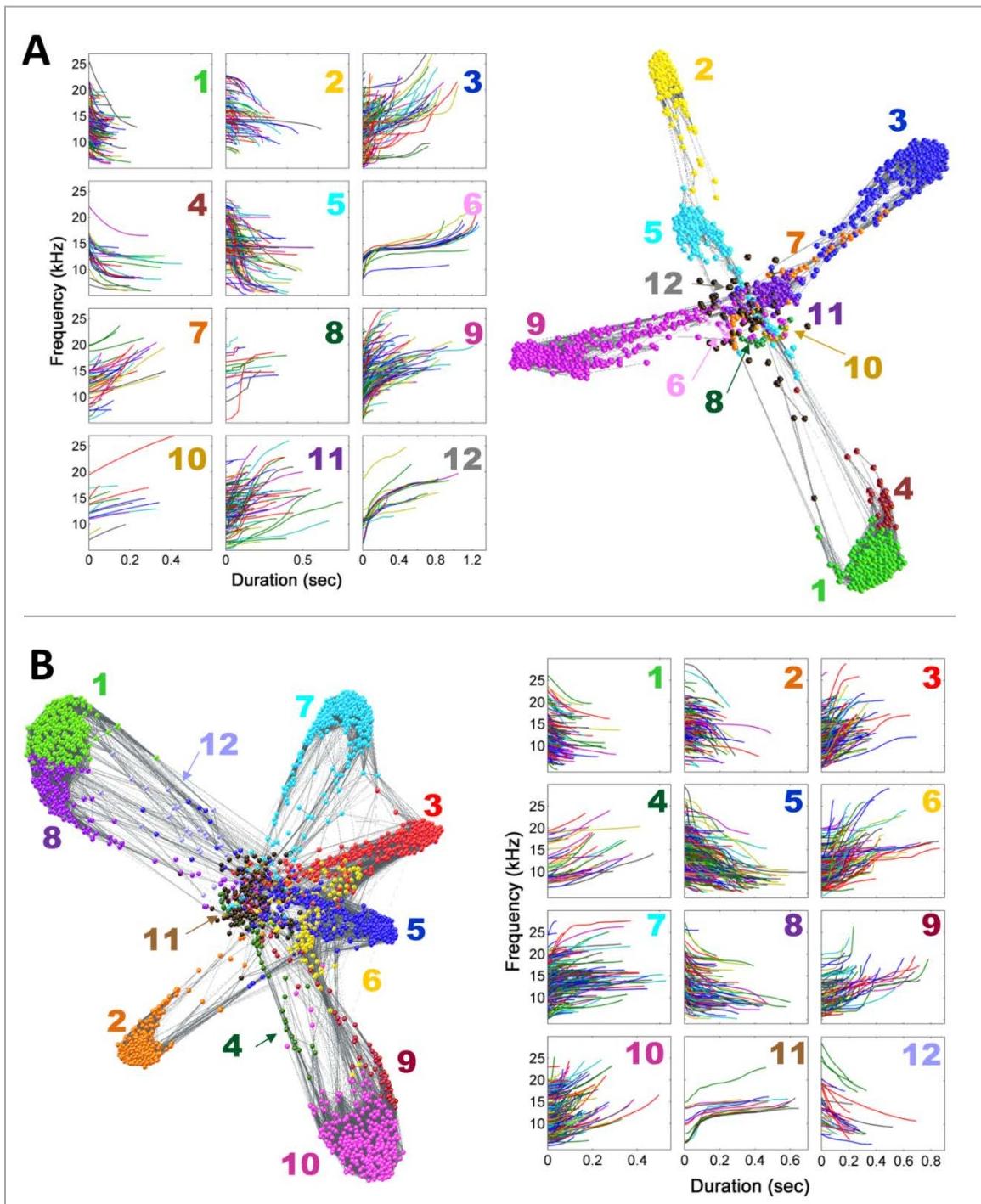


Figure 2. Visualization of whistle component clusters for spinner (upper) and common dolphins (lower). These clusters were automatically generated without the need to specify the number of possible clusters. The graphs show the association between nodes with longer connecting edges (lines) indicating higher dissimilarity. Nodes are color coded to display the automatically learned categories, and the grid next to each graph shows the whistles associated with each color. In each case, some whistle components (black) were not clustered.

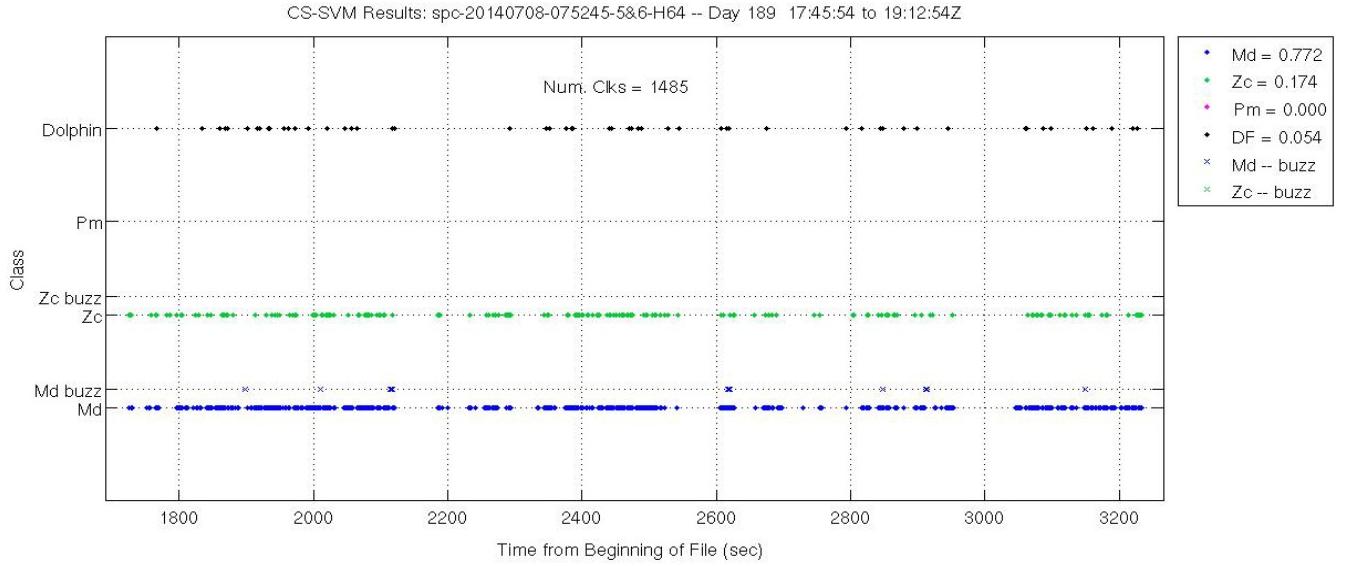


Figure 3: *Md buzz detected within the context of a foraging dive. Blue dots represent clicks classified as Md foraging clicks and blue x's are clicks that were classified as buzz clicks. Green dots are clicks that were (erroneously) classified as Zc.*

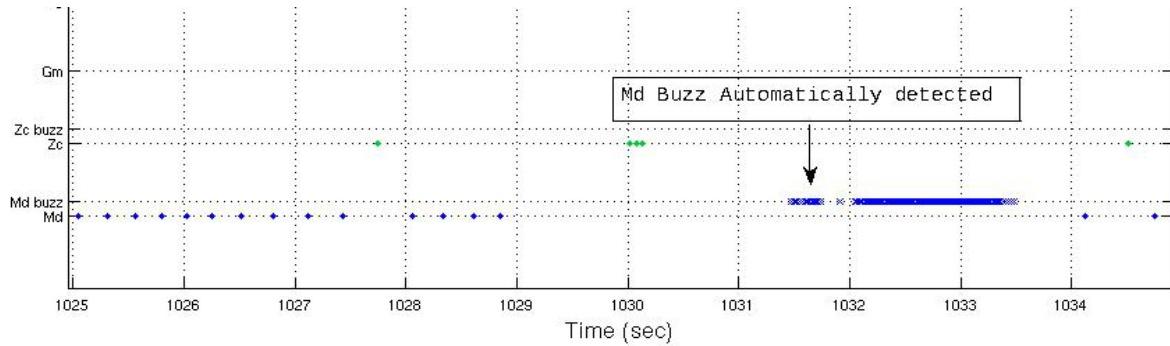


Figure 4: *The output of the CS-SVM classifier for a full Md dive recorded at AUTEC. Several buzzes were detected.*

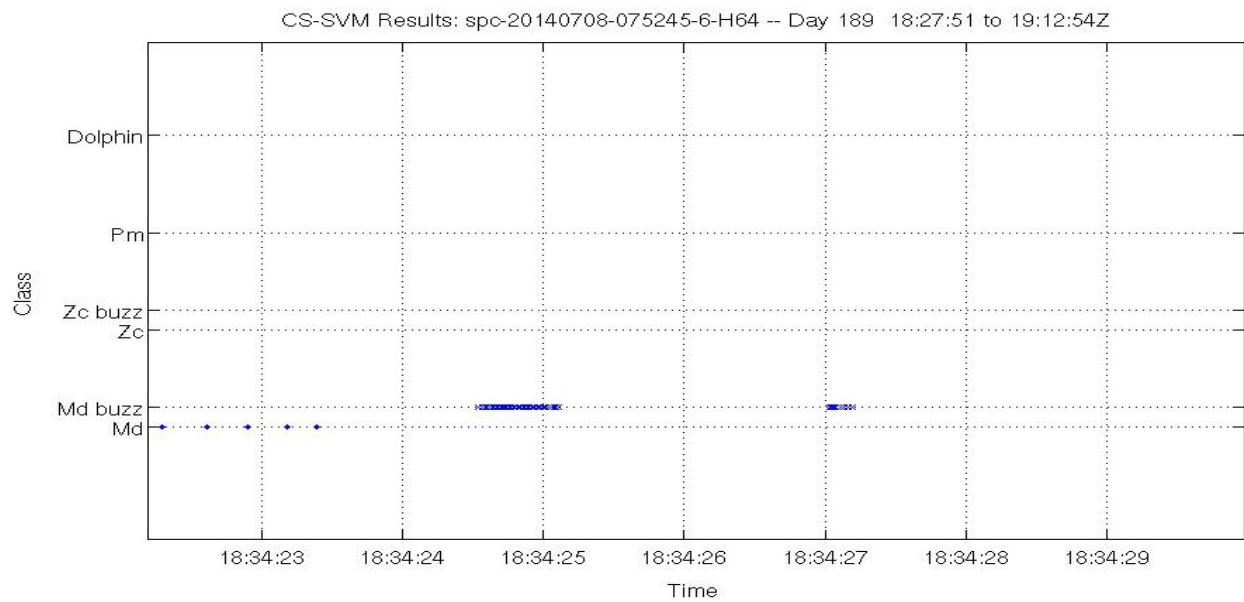


Figure 5: Close up of buzz detections from figure 2. Often, the whole buzz is not detected probably due to rapid head motion of the animal as it follows its prey just prior to capture.

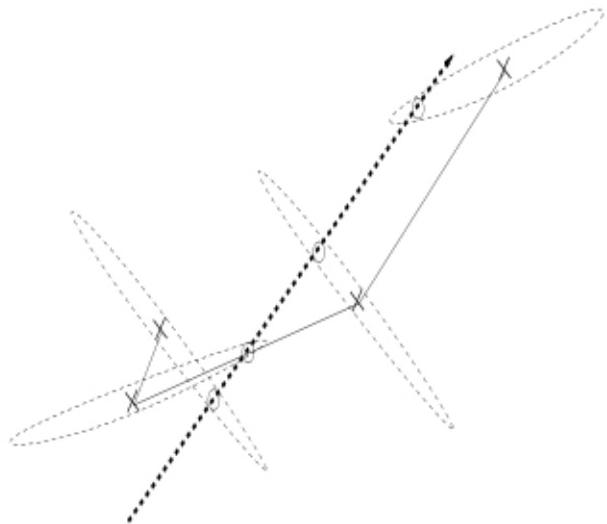


Figure 6: Example of tracking highly ambiguous localizations.

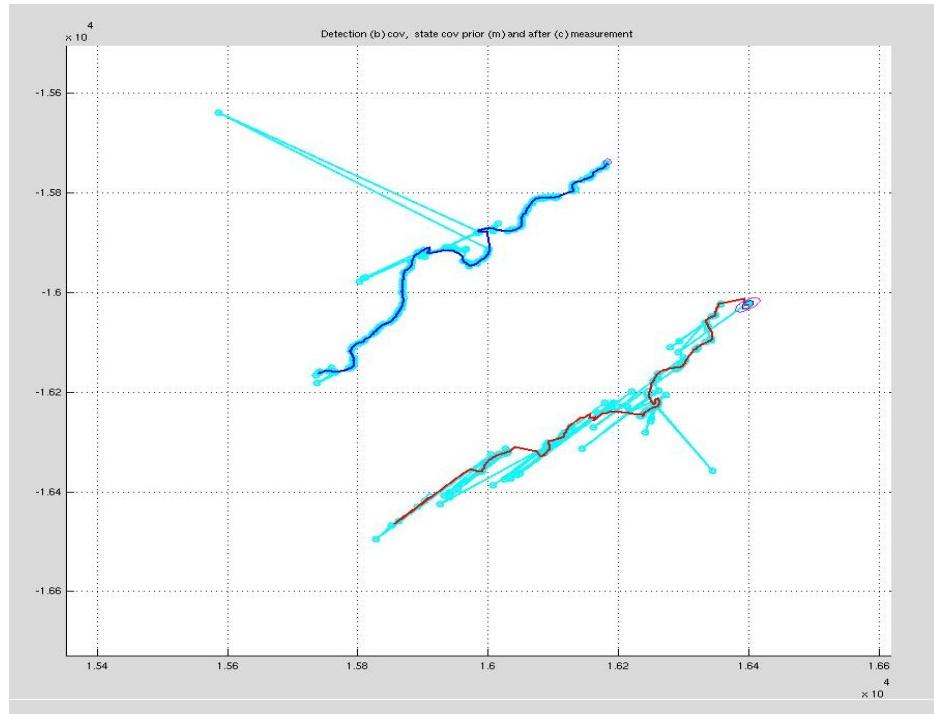


Figure 7: Output of MHT – Kalman filtering algorithm tracking for 2 Blainville's beaked whales (blue and red solid lines) using bottom-mounted hydrophones at AUTEC (cyan dots are raw localizations).

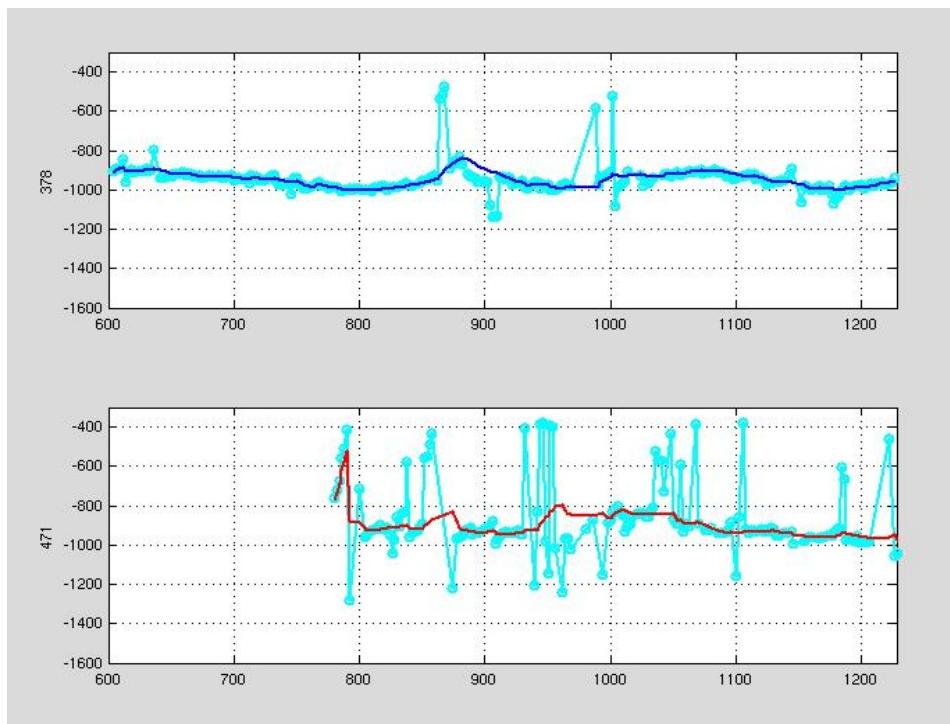


Figure 8: Depth tracks (blue and red solid lines) from the 2 Blainville's beaked whales in Figure 2. Cyan dots are raw depths.

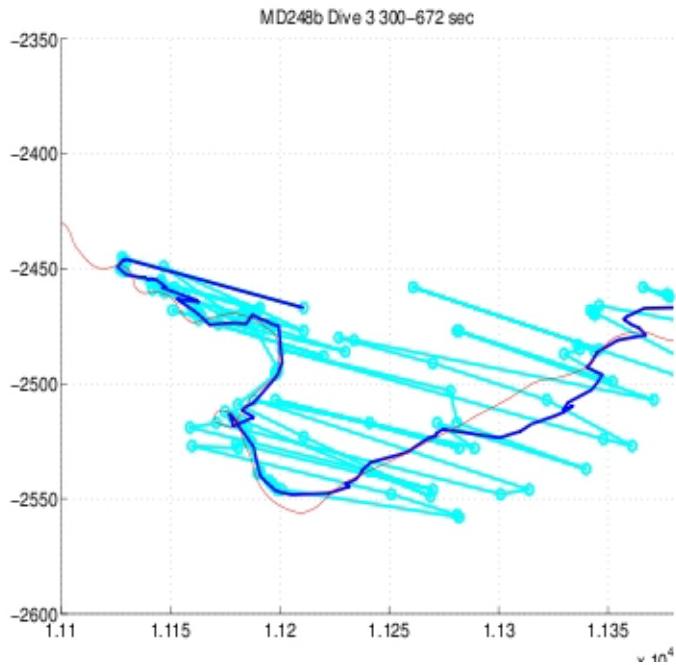


Figure 9: X-Y track from the MHT algorithm (solid blue line) for a segment of a Blainville's beaked whale dived recorded on a DTAG. The red line represents the ground truth position recorded by the tag and the cyan dots are the raw localizations.

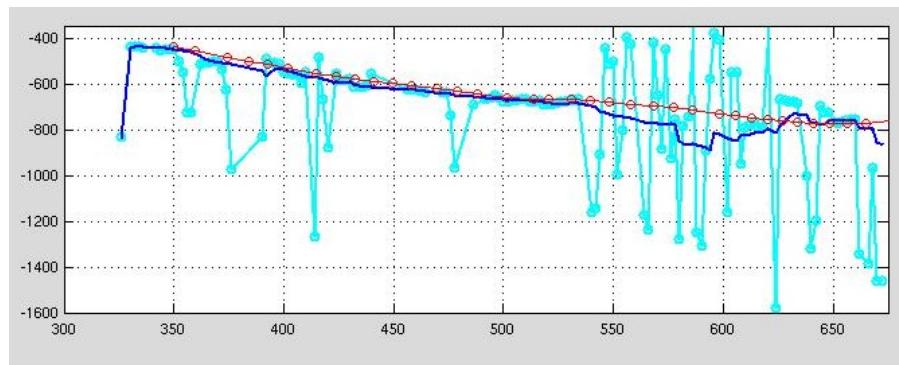


Figure 10: Depth track for the whale in figure 4. Solid blue line represents the output of the MHT tracker, the red line represents the ground truth depth recorded by the tag and the cyan dots are the raw depths.